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Fuel Consumption Prediction in Shovel-Truck System of Surface Mine Using Artificial Neural Network

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Abstract

The operations of a mine revolve around the budget, which describes the concept of cost of operations and returns generated. The fuel expended by each mining truck varies depending on differing conditions and is therefore difficult to be estimated based solely on manufacturers' manuals. Most mining companies have challenges forecasting the anticipated fuel consumption which has an essential influence on the budget. Usually, there is an under or overestimation of fuel consumed which goes beyond the stipulated allowable limits. BCM International Limited, Nzema, faces difficulties in accurately estimating fuel consumption for planning and budgeting purposes. A review of previous studies has shown that the Backpropagation Neural Network (BPNN) is a method noted for fuel consumption prediction. However, the prediction capability of the BPNN is dependent on the type of training algorithm used for the weight adaptation and bias assignment. Because of that, this study applied and tested three training algorithms namely the Levenberg Marquardt (LMA), Bayesian Regularisation (BRA) and the Scaled Conjugate Gradient (SCGA) to build an Artificial Neural Network (ANN) model to predict truck fuel consumption at BCM International Limited. The motive here was to select the best-performing training algorithm. It was deduced that the LMA produced the best model results with the least Mean Absolute Percentage Error (MAPE) value of 10.63% followed by SCGA and BRA. The model testing also revealed that the fuel consumed can be predicted from the input elements by approximately 96% using the LMA, 87% by BRA and 83% by the SCGA. The optimum BPNN structure with the LMA was 3-48-1 describing an input of three variables, 48 neurons in the hidden layer and one output.

1.0 Introduction

The entire operations of a mine revolve around the concept of the cost of operations and how much returns can be generated.,. As explained by [1] a budget is a set of expectations set before the start of a particular project. The budget sets out the expected costs of operations for a period which has not yet started. The operations cost is the cost of resources used by the mine to achieve set targets and to maintain its existence. A model from [2] explains that about 50% of the operating costs of open pit mining is related to material loading and

haulage. In mining, haul trucks are used to carry material along haul roads to different locations within the mine. This haulage activity represents a large percentage of the overall cost of operation of the mine, specifically fuel consumption.

Major mining corporations carry out some research to estimate the amount of fuel anticipated to be used by haulage trucks. However, significant progress has not yet been achieved in this field of research due to the complexity of the parameters involved. Haul truck fuel consumption is a function of various parameters, the most significant of which have been identified and categorised into some groups such as fleet management, mine planning, modern technologies, haul road, design and manufacture, weather condition and fuel quality [3].

BCM International Limited formerly known as Bayswater Contracting operates as a mining and civil contractor by providing services in opencast mining, civil earthworks, and crushing. The company serves the mining industry in Sub-Saharan Africa and Central Asia. The company was founded in 1990 and is based in Accra, Ghana. BCM International Limited took over Endeavour Mining Corporation, Nzema in December 2017 [4]. The mining method is still the conventional open pit mining including drilling, blasting, loading and hauling operations which previously was being carried out by African Mining Services (AMS) under the control of Endeavour Mining Corporation. Presently, active mining is ongoing on the Salman Trend on oxide and upper transition material. Waste and near-pit ore haulage is mainly conducted by 777E, 777D and 773D trucks; and material hauled out of smaller satellite pits utilises articulated Volvo dump trucks.

A powerful, invaluable financial management and budget planning instrument for mine sites is the use of plan versus actual, to improve prediction capabilities regarding capital and operating cost structures. Harnessing the ability to predict the financial implications of changes in the mining environment is of critical importance to a mining company's success [5].

Most often, mining companies have challenges in making a forecast about the amount of fuel projected to be consumed in loading and hauling. The fuel expended by a truck varies depending on several factors such as haul road profile, haulage distances and speed. Because of this, fuel consumption is difficult to be established based on the mining truck manufacturers' manuals and estimates. In most cases, there is an underestimation or overestimation of the fuel consumed beyond the allowable limit stipulated in the budget and forecast.

BCM International Limited, Nzema Mine, located in the Western Region of Ghana, uses the shovel-truck system for loading and hauling operations and like most mining companies, faces difficulties in accurately estimating fuel consumption for planning and budgeting purposes. The company has made several attempts to estimate the fuel consumed by statistically analysing historical data on fuel consumption over time.

In this paper, an artificial intelligence (AI) model is developed to predict the fuel consumption of the shovel-truck system at BCM International Limited, Nzema Mine. In literature, several methods are being adopted to predict fuel consumption. Notable among them is the Backpropagation Neural Network (BPNN) method. However, the prediction capability of the BPNN is dependent on the type of training algorithm used for the weight adaptation and bias assignment. In this study, three different training algorithms were

employed to build an Artificial Neural Network (ANN) model, specifically BPNN, to predict the fuel consumption of the shovel-truck system at BCM International Limited. The purpose is to select the best-performing training algorithm for fuel consumption prediction in the study area.

The objective of the paper is to establish key parameters that affect fuel consumption and their correlation using the Artificial Neural Network technique with different training algorithms to predict fuel consumption to select the best-performing training algorithm.

2.0 Methodology

A backpropagated ANN model was developed to predict the amount of fuel to be consumed using some key factors affecting fuel consumption. Several methods were used in a bid to develop the model. These include:

i. selection of training and testing data;

ii. choice of data pre-processing techniques;

iii. model construction and component selection;

iv. the training and tuning process; and

v. other domain specific techniques that can be leveraged in order to achieve a good result.

The model is based on a certain amount of traffic data. First, a Mapstd algorithm in Matlab was used to normalise the inputs to be fed into the ANN from the raw data. The model was then built with codes and scripts in Matlab. Next, the prediction of fuel consumption of representative vehicles was based on training algorithms. Finally, the trained Backpropagation algorithm was applied to a new test data in order to obtain a high confidence level of minimal error with respect to fuel consumption prediction.

2.1 Data Collection and Description

ANNs are only as good as the input data used to train them. The effect on the ANN's performance can be significant if important data points are missing [6]. Explanatory variables used in this study as the inputs are: payload, count of trips made and worked hours. The response variable that served as the output was the amount of fuel consumed in a month. Monthly data on equipment statistics were collected from June 2018 to August 2019 from BCM Site. All data taken were from similar equipment of around the same age, type, model and make and started work concerning this study on the same available date. The dataset used for this study consisted of a total of 432 records of payload, count of trips made, and worked hours and fuel consumed by Caterpillar 777D dump trucks obtained from BCM Ghana Limited, Nzema Mine.

2.2 Data Pre-processing

The data used in this study were normalised into the scale interval of [0, 1] with the Mapstd technique as part of the preparations for training the network. A fully normalised database

allows its structure to be extended to accommodate new types of data without much change to an existing structure. As a result, applications interacting with the database are minimally affected, and redundancy and dependency of data are reduced, while the integrity and performance of the query are increased. According to [7], the goal of normalisation is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the range of values. Results from [8] explains that in this technique of data normalisation, a linear transformation is performed on the original data. The minimum and maximum values from data were fetched and each value was replaced according to Equation (1).

$$V' = \frac{V - \min(A)}{\max(A) - min\,(A)} \tag{1}$$

where A is the attribute data; min(A), and max(A) are the minimum and maximum absolute values of A respectively; V′ is the new value of each entry in data; and V is the old value of each entry in data. The normalisation of the data which were payload, count of trips made, worked hours and amount of fuel consumed in a month was done using codes written in Matlab software. In the Matlab environment, this technique is known as mapstd. If mapstd was used to scale the targets, then the output of the network was trained to produce outputs with zero mean and unity standard deviation. The data used in this study were subjected to sensitivity analysis to find the degree of influence and relative importance of the input variable values to the output variable using the Pearson correlation coefficient (Equation (2)).

$$r_{ij} = \frac{\sum_{j=1}^{m}\left(X_{ij} - \bar{X}_i\right)\left(Y_j - \bar{Y}\right)}{\sqrt{\sum_{j=1}^{m}\left(X_{ij} - \bar{X}_i\right)^2 \sum_{j=1}^{m}\left(Y_j - \bar{Y}\right)^2}} \tag{2}$$

Here, Xij and are the jth and average values of the ith input parameter respectively, Yj denotes the jth value of the dependent parameter and ȳ denotes the average value of the predicted fuel consumed. It is worth noting that, the higher the R-value, the more the relative impact of that input parameter on the output [9].

Multicollinearity analysis was carried out to establish the association between the input and output parameters. Multicollinearity is a problem that affects models in which one or more of the regressors are highly correlated with linear combinations of other regressors. The degree of multicollinearity is usually measured separately for each regressor by comparing two quantities. The ratio between these two quantities (actual/hypothetical variance) is called Variance Inflation Factor (VIF) and it measures how much the linear correlation of a given regressor with the other regressors increases the variance of its coefficient estimate concerning the baseline case of no correlation and is given in Equation (3) [10].

$$VIF_j = \frac{1}{1 - R_j^2} \quad (3)$$

The main purpose of system design is to resolve the structure of the ANN, the backpropagation algorithm and the learning rule. This phase also involves partitioning the data collected into two distinct subsets to use during the training and testing processes. The first portion of data is the training subset which is used to update the weights of the network in the training phase. The test subset is used during the learning process to check the network response for untrained data. The data used in the test subset are distinct from those used in the training; however, they lie within the training data boundaries. Architecture may be changed based on the performance of the ANN on the test subset. In a neural network model, the training dataset is used to obtain the network weights and develop the model. The validation subset includes examples different from the training and testing subsets. A validation subset is used after selecting the best network through the learning process to further examine the network capability of generalization [10]. In this research, the data was partitioned into 80% and 20% of the total data as training and testing respectively.

2.2 Network Structure

The structure of the proposed ANN model for function approximation is a Backpropagation Neural Network (BPNN) with 3 input layers with the hidden neurons in the hidden layer set from one to sixty and an output layer. In this research, function fitnet was used to generate the BPNN structure. As written in the MATLAB language, fitnet(hiddenSizes, trainFcn) takes a row vector of N hidden layer sizes, and a backpropagation training function, and returns a feed-forward neural network with N+1 layers. Figure 1 is a flowchart for the BPNN model development.

ANNs are desirable resolutions for composite problems as they can interpret the compound associations between the multiple parameters involved in a problem. This paper presents the development of a trained back propagated multi-layer perceptron artificial neural network model to determine the fuel consumption of haul trucks in a surface mine.

Network training is the most important part of ANN modelling. During the training phase, the training data was fed into the input layer which uses a learning algorithm to adjust its parameters to attain the desired output. Each input was multiplied by its connected weight and in the simplest state, these quantities and biases were combined; they were then passed through the training function to produce the output. An illustration of the network training process is presented in Figure 2.

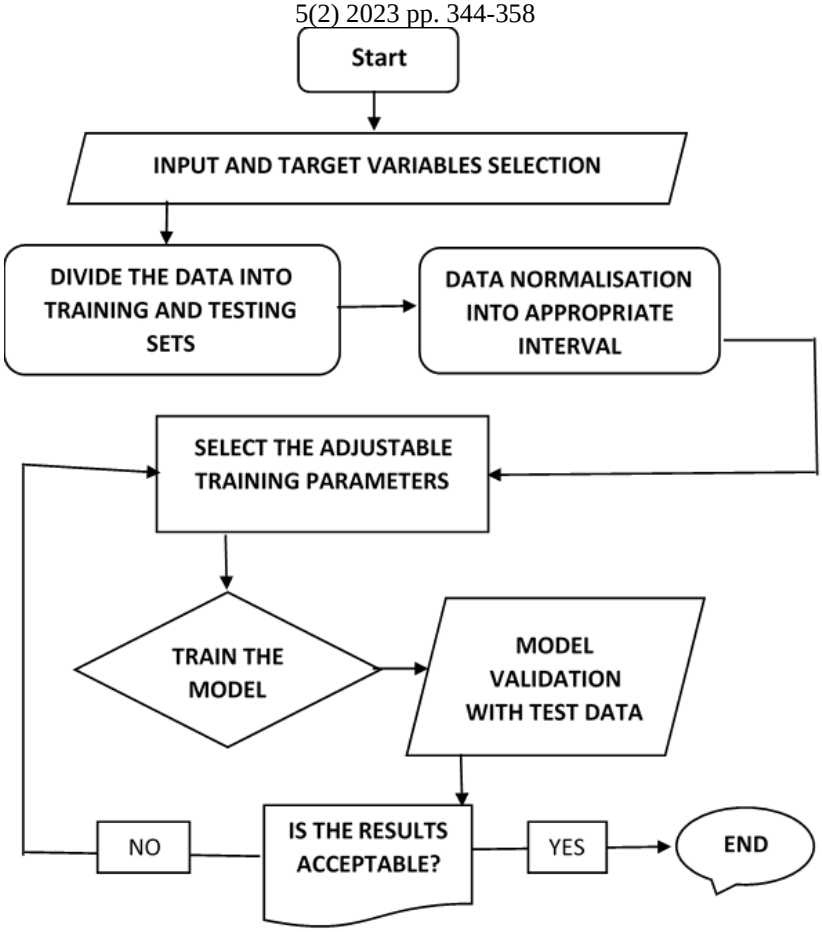

Figure. 1: Training the Model

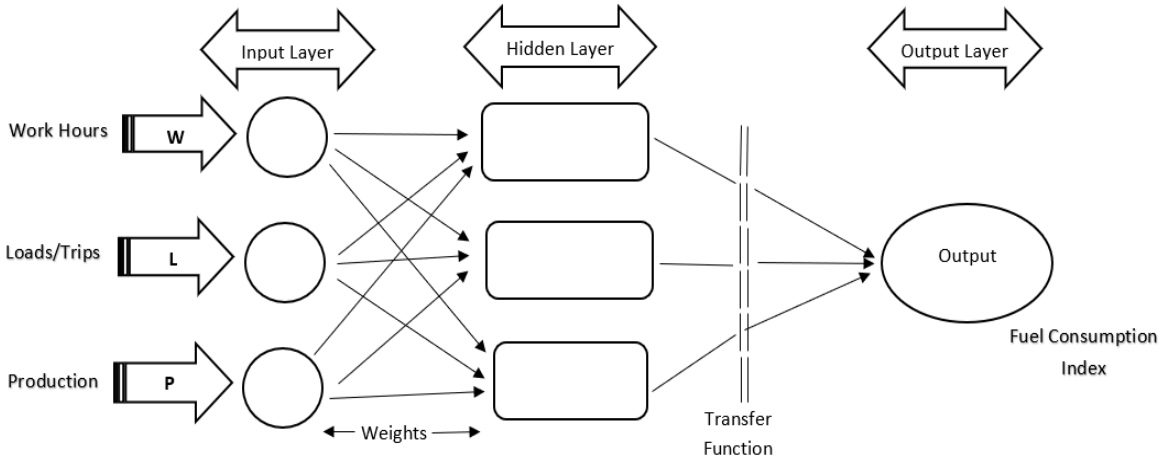

Figure 1 Training of the Backpropagation Neural Network

The procedure used to carry out the learning process in a neural network is the optimisation or learning algorithm. There are different types of training algorithms which are used in training a BPNN. The choice of algorithm depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the

network, the error goal, and what exactly the network is being used for. This study used three backpropagation training algorithms; the Levenberg Marquardt, Bayesian Regularisation and the Scaled Conjugate Gradient.

It is crucial to select a suitable performance measure when validating a model. These models help to support decision-making for a wide range of data sets. In this study, the model performance measurements that were employed are the Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). Statistical indicators of Correlation Coefficient (R), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Normalised Root Mean Square Error (NRMSE) were also considered to examine the error and performance of the BPNN output.

The *Mean Absolute Percentage Error* (MAPE) measures the size of the error in percentage terms. The MAPE is a statistical measure of determining the accuracy of a forecast system. It measures this accuracy as a percentage and can be calculated as the average absolute per cent error for each period minus actual values divided by actual values [11]. This is given in Equation (4) where At is the actual value and Ft is the forecast value.

$$M = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \qquad (4)$$

The *Correlation Coefficient*(R) tells how closely data in a scatter plot fall along a straight line. The closer the absolute value of R is to one, the better the description of the data by a linear equation. Data sets with values of R close to zero show little to no straight-line relationship [12]. Matlab syntax R = corrcoef(X, Y) which returns the correlation coefficient value if you have 2 variables X and Y was used.

The Coefficient of Determination (R^2) is a key output of regression analysis. It is interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variable. The R^2 for a linear regression model with one independent variable is Equation (5) as:

$$R^2 = \{ (1 / N) * \Sigma [(xi - x) * (yi - y)] / (\sigma x * \sigma y) \}2 \qquad (5)$$

where *N* is the number of observations used to fit the model, Σ is the summation symbol, *xi* is the *x* value for observation *i*, *x* is the mean *x* value, *y*i is the *y* value for observation *i*, *y* is the mean *y* value, σx is the standard deviation of *x*, and σy is the standard deviation of *y* [13].

The Root Mean Square Error (RMSE) is a measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. The RMSE serves to aggregate them into a single measure of predictive power. It is expressed in Equation (6) as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \quad (6)$$

where X_{obs} is observed values and X_{model} is modelled values at time/place i[14]

Non-dimensional forms of the RMSE such as

Normalised Root Mean Square Error (NRMSE) are useful because often one wants to compare RMSE with different units [15. This is expressed in Equation (7) as

$$NRMSE = \frac{RMSE}{X_{obs,\max} - X_{obs,\min}} \quad (7)$$

This paper presents a study in which different types of algorithms were examined to determine the best backpropagation training algorithm that can best predict the fuel consumed. Other tests were also carried out to affirm the effectiveness and performance of the techniques that were used in this work.

Building the Network

To train the model, monthly data on equipment statistics were collected from June 2018 to August 2019 from BCM Mine Site. All data taken were from trucks of around the same age and make. From the data collected, the values of worked hours, loads, and production in bank cubic meter (BCM) (volume of material *insitu*) produced per month were used to calculate the fuel consumption and used to train

the model. Using the network structure presented earlier as the basis, three training algorithms; the Levenberg Marquardt Algorithm, the Bayesian Regularisation Algorithm and the Scaled Conjugate Gradient Algorithm were applied. The first part of the network used 80 % of the data for training the model and the latter part used the remaining 20 % of the data for testing the model. The fuel consumed data was set as the observed values against which the predicted values will be measured. The error margin between the observed and predicted values was calculated for each neuron number. The model performance criteria were applied to evaluate the validity and performance of the networks.

3.0 Results and Discussion

Results from the sensitivity analysis test that was done on the input parameters to measure how strong a relationship is between two variables are shown in Figure 3. It can be observed that all the parameters had a positive impact on the resulting fuel consumption. From the values, it can be seen that worked hours were the controlling parameter on the net fuel consumption, followed by loads and then finally production.

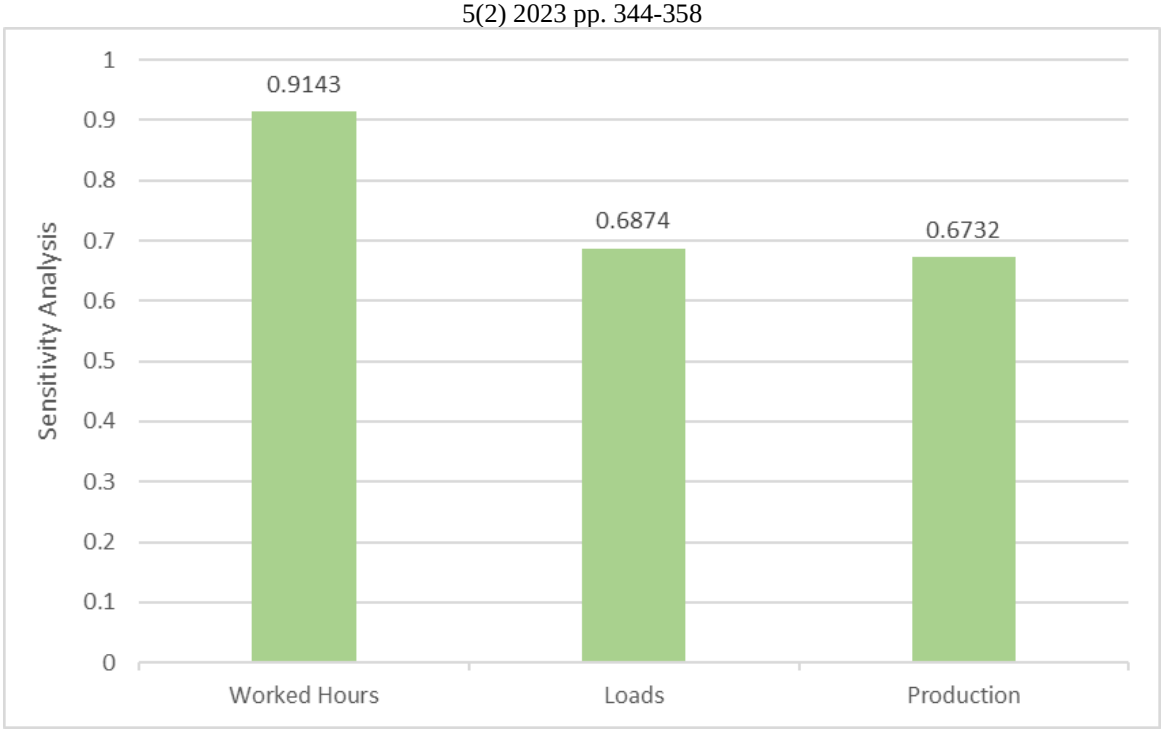

Figure 3: Sensitivity Analysis for the BPNN Model

Multicollinearity is tested with the help of tolerance and it's reciprocal, called Variance Inflation Factor (VIF) [16]. The numerical value for VIF tells you (in decimal form) what percentage of the variance is inflated for each coefficient. The more the VIF increases, the less reliable the regression results. In general, VIFs range from 1 to upwards. Table 1 presents the VIF results for input parameters. It can be observed from Table 2 that production and loads gave values of 3.32 and 3.27 respectively. This implies that they correlate moderately with other input parameters. Worked hours gave a VIF value of 4.18 which indicate that it is more correlated with at least one of the input parameters. VIF measures how much of the variation in one variable is explained by the other variable. As stated in [8], it is a rule of thumb that a VIF of 1 indicates the non-existence of multicollinearity among input parameters. Moreover, a VIF greater than 1, means input parameters may be moderately correlated. A VIF between 5 and 10 indicates a high correlation that may be problematic. And if the VIF goes above 10, multicollinearity becomes a problem which must be handled accordingly.

Table 1 Multicollinearity Test for the AI Model

	Loads	Worked Hours	Production
Variance Inflation Factor (VIF)	3.32	4.18	3.27

3.1 The Levenberg Marquardt Algorithm

The Levenberg Marquardt Algorithm (LMA) used the three input variables, one hidden layer and one output variable both in the model training and testing stages. The number of neurons used in the hidden layer was increased from 1 to 60. The optimal model to predict the fuel consumed with the most minimal error was [3-48-1]. This explains an input of three variables,

with 48 neurons in the hidden layer resulting in one output element. A summary of the optimum results for the Levenberg Marquardt algorithm is presented in Table 2.

Table 2 Results of the Optimal Model for the Levenberg Marquardt Algorithm

Model Stages	MAPE (%)	NRMSE	R^2	R
Training	14.787	0.067	0.935	0.967
Testing	10.636	0.055	0.963	0.981

In Table 2, the training model produced results with the lowest MAPE value of approximately 14.79% whilst the testing model produced 10.64% as the minimum MAPE value. The statistical measure that calculates the strength of the relationship between the actual and predicted values, R was found to be above 0.9 but less than 1 in all training and testing carried out with their respective neuron numbers. This indicates a strong relationship between the predicted outputs and the actual when the Levenberg Marquardt Algorithm was applied. Hence producing reliable prediction of fuel consumption. In the case of NRMSE, the best value of 0.067 was achieved during the training of the model and 0.055 after testing the model. These values of the NRMSE indicate a better fit since they are approaching zero. The R^2 was computed to be 0.935 and 0.963 during the training and testing stages of the model. The R^2 obtained is a very good value which indicates that the dependent variable (fuel consumed) can be predicted with minimal error from the independent variables (inputs). Interpreting the training stage, it can be concluded that about 93.5% of the fuel consumed is predictable from the input elements. Similarly, the tested built model indicates that the fuel consumed can be predicted from the input elements by approximately 96.3%.

3.2 The Bayesian Regularization Algorithm

The summary of the optimal results of the processed data using the Bayesian Regularisation Algorithm (BRA) is illustrated in Table 3.

Table 3. Results of the Optimal Model for the Bayesian Regularisation Algorithm

Model Stages	MAPE (%)	NRMSE	R^2	R
Training	16.974	0.087	0.890	0.943
Testing	16.010	0.111	0.869	0.932

In the implementation of the BRA, the neurons used in the hidden layer were set from 1 to 60. The BRA produced results with a minimum training MAPE of 16.97%. The least MAPE value recorded from the model testing was 16.01%. The R obtained from this algorithm was also found to be above 0.9 but less than 1 in both training and testing. This shows that there is a strong association between actual and predicted fuel consumption. The NRMSE obtained for the

trained model was 0.087 whilst 0.111 was produced when the model was tested. The NRMSE can be interpreted as a fraction of the overall range that is typically resolved by the model with lower values indicating better fit. The training and testing R^2 values were 0.890 and 0.869 respectively. The R^2 obtained is a very good value which shows that the output (fuel consumed) can be predicted with minimal error from the input variables. That is, 89% of the fuel consumed can be predicted concerning the training and approximately 87% of the test data could be adequately predicted. The optimum model using the BRA was [3-36-1]. This means an input of three variables, with 36 neurons in the hidden layer resulting in one output element.

The summary of the optimal results of the processed data is illustrated in Table 4 after using the Scaled Conjugate Gradient Algorithm (SCGA).

Table 4 Results of the Optimal Model of the Scaled Conjugate Gradient Algorithm

Model Stages	MAPE (%)	NRMSE	R^2	R
Training	15.025	0.089	0.887	0.942
Testing	14.048	0.116	0.835	0.914

The (SCGA) produced test results (Table 4) with a minimum MAPE value of 15.02% for the training and 14.05% after the built model was tested. The R obtained by the SCGA was found to be above 0.9 but less than 1 in both training and testing respectively. This shows that there is a strong association between the predictions and the actual. The NRMSE calculated values for both training (0.089) and testing (0.116) indicate a better fit. The R^2 obtained shows that in the training model, about 88.7% of the fuel consumed is predictable from the input elements while 83.5% was the prediction level obtained at the testing stage. The SCGA best-predicted model was [3-17-1]. This describes an input of three variables, with 17 neurons in the hidden layer resulting in one output element as the optimal model to best predict the fuel consumed with the most minimal error.

3.3 Comparison of the Backpropagation Training Algorithms

Analysis of all the test results indicated that the LMA had the least MAPE value of 10.63% as compared to 16.01% and 14.05% achieved by the BRA and SCGA respectively. This implies that the LMA prediction is marginally deviating from the observed with an absolute error margin of 10.63%. Figure 4 shows how the prediction accuracy of each of the training algorithms fared each other.

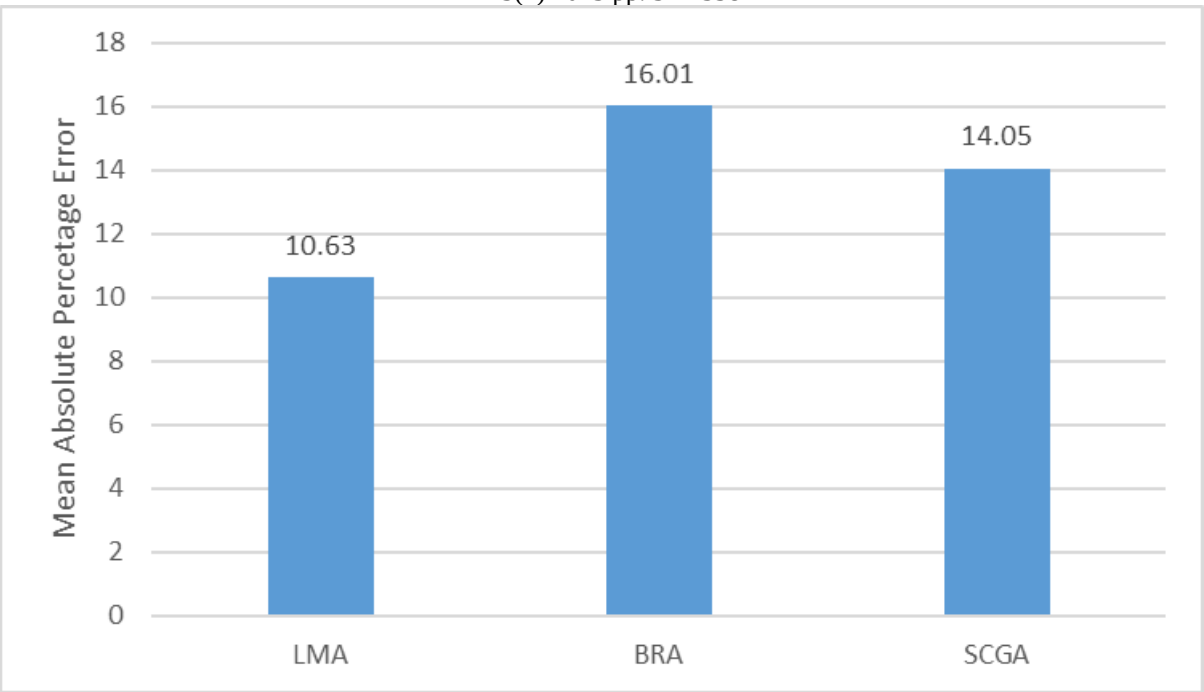

Figure 4: Prediction Accuracy of the Training Algorithms

LMA had an R-value of 0.981 whereas BRA and SCGA had values of 0.932 and 0.914, respectively. Based on the R results, it can also be interpreted that the LMA can produce a prediction accuracy of about 98.1% when compared to the BRA and SCGA which had 93.2% and 91.4% respectively. The R results further depict the strength of linear dependency between the observed and predicted outcomes from the model. The predicted values produced when LMA was applied in the BPNN are in close agreement with the observed data than the other methods. Based on the R^2 test results, it can be stated that the LMA predictions can explain approximately 96% of the observed data while the BRA and SCGA achieved approximately 87% and 84%, respectively as shown in Figure 5.

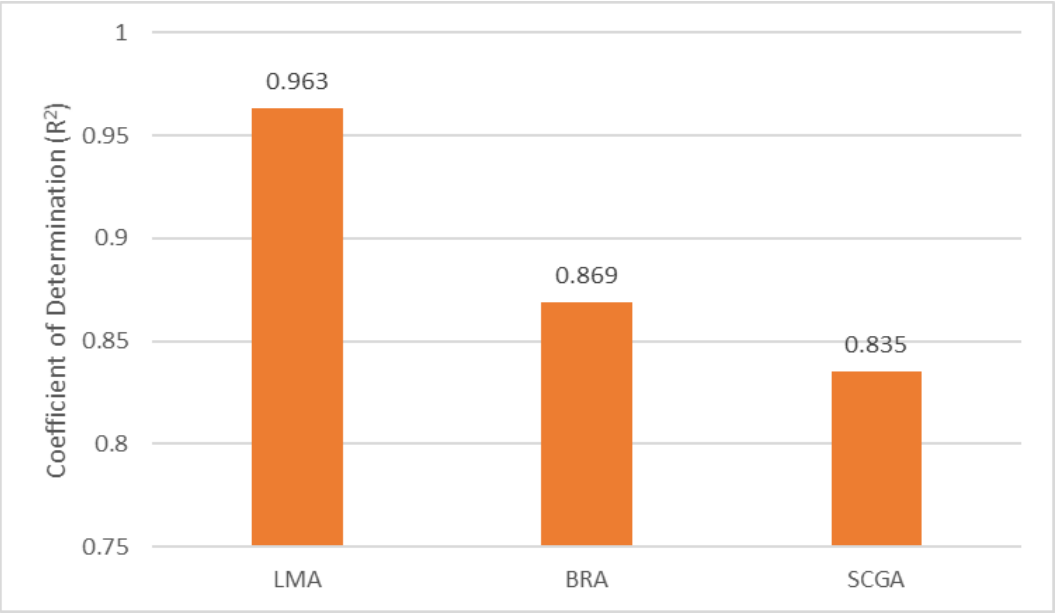

Figure 5: Prediction Relationship between Input and Output Data for each Algorithm

Theoretically, a model with lower NRMSE values indicates less residual variance. That is, the lower the NRMSE value the better the model performance. The obtained results show that the LMA had the least residual variances as compared with BRA and SCGA. From the NRMSE results, it can be deduced that the unexplained variability in the predicted fuel consumed when compared with the measured was very marginal. This is shown in Figure 6.

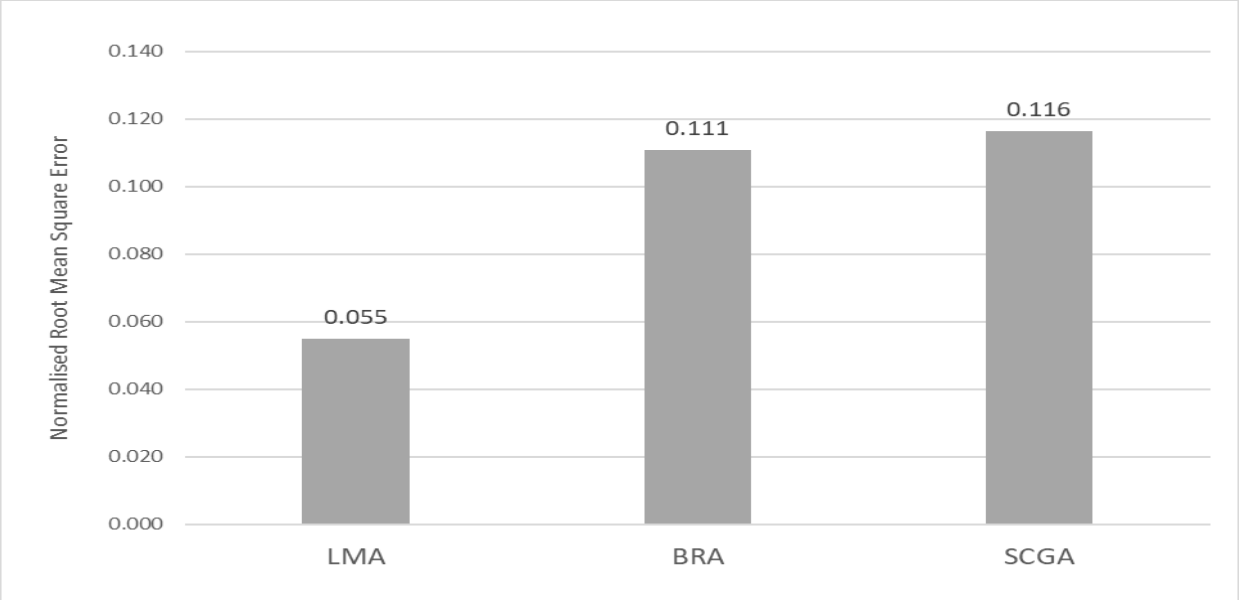

Figure 6: Residual Variances between Algorithms

4.0 Conclusions

This paper developed an AI-based interface to predict fuel consumption with a Ghanaian mine as the study area. A backpropagation neural network was applied making use of three different training algorithms; the Levenberg Marquardt, Bayesian regularisation and the scaled conjugate gradient to help arrive at the best model to aid in the prediction of the fuel consumed in a shovel-truck system with the most minimal error and the best relationship between parameters. The models were tested using the remaining dataset that was not used during the model development process.

The overall statistical analysis performed indicated which one out of the three training algorithms applied, has the best prediction results and the best relationship between parameters. It was found that the Levenberg Marquardt algorithm produced the model results with the most minimal error with a MAPE value of 10.63% after model testing, followed by the scaled conjugate gradient and then lastly the Bayesian regularisation. After testing the model, it was noted the fuel consumed can be predicted from the input elements by approximately 96% using the Levenberg Marquardt, 87% by the Bayesian regularisation, and 83% by the scaled conjugate gradient. The Levenberg Marquardt proved to be an effective backpropagation training algorithm for fuel consumption prediction with the best model prediction architecture of [3-48-1]. This describes an input of three variables, with 48 neurons in the hidden layer resulting in one output element. A sensitivity test carried out revealed that all the input variables had relative

importance and influence on the target variable. The multicollinearity analysis test showed that all the input variables were not redundant and as such were essential elements in the model prediction performance.

1

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